

## Remote sensing of crop residue cover and soil tillage intensity

C.S.T. Daughtry<sup>a,\*</sup>, P.C. Doraiswamy<sup>a</sup>, E.R. Hunt Jr.<sup>a</sup>, A.J. Stern<sup>a</sup>,  
J.E. McMurtrey III<sup>a</sup>, J.H. Prueger<sup>b</sup>

<sup>a</sup> USDA-ARS Hydrology and Remote Sensing Laboratory, Bldg. 007, Room 104,  
10300 Baltimore Ave., Beltsville, MD 20705-2325, USA

<sup>b</sup> USDA-ARS National Soil Tilth Laboratory, 2150 Pammel Drive, Ames, IA 50011-4420, USA

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### Abstract

Management of plant litter or crop residues in agricultural fields is an important consideration for reducing soil erosion and increasing soil organic C. Current methods of quantifying crop residue cover are inadequate for characterizing the spatial variability of residue cover within fields or across large regions. Our objectives were to evaluate several spectral indices for measuring crop residue cover using satellite multispectral and hyperspectral data and to categorize soil tillage intensity in agricultural fields. Landsat Thematic Mapper (TM) and EO-1 Hyperion imaging spectrometer data were acquired over agricultural fields in central Iowa in May and June 2004. Crop residue cover was measured in corn (*Zea mays* L.) and soybean (*Glycine max* Merr.) fields using line-point transects. Spectral residue indices using Landsat TM bands were weakly related to crop residue cover. With the Hyperion data, crop residue cover was linearly related to the cellulose absorption index (CAI), which measures the relative intensity of cellulose and lignin absorption features near 2100 nm. Coefficients of determination ( $r^2$ ) for crop residue cover as a function of CAI were 0.85 for the May and 0.77 for the June Hyperion data. Three tillage intensity classes, corresponding to intensive (<15% residue cover), reduced (15–30% cover) and conservation (>30% cover) tillage, were correctly identified in 66–68% of fields. Classification accuracy increased to 80–82% for two classes, corresponding to conventional (intensive + reduced) and conservation tillage. By combining information on previous season's (2003) crop classification with crop residue cover after planting in 2004, an inventory of soil tillage intensity by previous crop type was generated for the whole Hyperion scene. Regional surveys of soil management practices that affect soil conservation and soil C dynamics are possible using advanced multispectral or hyperspectral imaging systems.

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### 1. Introduction

Soils can function as either sources or sinks for atmospheric CO<sub>2</sub> depending on several factors includ-

ing soil properties, land use and management. The potential for C sequestration in soils is significant based on presumed recapture following the large decreases in soil organic C that occurred when native forests and grasslands were converted to agriculture (Lal et al., 1999). Depletion of soil C is accentuated by soil degradation and intensified by soil mismanagement. Long-term use of conservation tillage practices can lead to increased soil organic matter, improved soil structure and increased aggregation compared to intensively

\* Corresponding author. Tel.: +1 301 504 5015;  
fax: +1 301 504 8931.

E-mail address: [cdaughtry@hydrolab.arsusda.gov](mailto:cdaughtry@hydrolab.arsusda.gov)  
(C.S.T. Daughtry).

tilled soils (Rasmussen and Rohde, 1988). Adoption of appropriate conservation and restoration practices can build up soil organic C by preserving the input of C through crop residue and by decreasing C loss from soil erosion (Lal, 2004).

Since changes in soil organic C occur slowly, biogeochemical models simulating C dynamics are often used to predict net C sequestration for different soil types and land management. These models of C dynamics range from simple empirical applications-oriented models to complex research-oriented models (Ma and Shaffer, 2001). Empirical models correlate ecosystem-scale processes with parameters that are readily measured in the field and, as a result, may simplify some important functional relationships. Biogeochemical models emphasize the underlying biological, chemical and physical processes that control C transformations, but tend to be localized (i.e., point-based) because of their detailed input data requirements.

Linkage of biogeochemical models to geographic information systems (GIS) has blurred the spatial-scale distinction between empirical and process models. However, the lack of appropriate data to support these process models across a wide range of soil and land management scenarios continues to be a major issue limiting their usability (Ma and Shaffer, 2001). Crop management and soil tillage practices vary spatially (field to field) and temporally (year to year) as individual growers adjust their management strategies to changing economic and environmental conditions. Robust approaches for extending process C models from isolated points to landscape and regional scales have not been identified and evaluated. While current remote sensing techniques cannot directly monitor soil C dynamics, recent advances in remote sensing of soils and crop residues can potentially provide some of the spatially variable biophysical parameters needed by these models to predict C dynamics across landscapes.

Spectral reflectance of soils is primarily determined by moisture, iron oxides, organic matter, particle-size distribution, mineralogy and soil structure (Baumgardner et al., 1985). In perhaps the most comprehensive study of the reflectance of soil, Stoner and Baumgardner (1981) defined five general classes of soil reflectance spectra and identified organic matter and iron oxide contents as the primary factors determining shape of the reflectance spectra. Soil reflectance generally increased as soil moisture, particle-size, surface roughness, organic matter content and iron oxide content decreased. Spectral reflectance is strongly correlated with organic matter content among soils from the same

parent materials; however, the relationship is sensitive to changes in iron and manganese oxides in soils from different parent materials.

Remote sensing as aerial photography has been a tool in the mapping of soils for more than 50 years. The synoptic view of the soil in the landscape and the tonal variations in photographs and multispectral images enhanced the delineation of soil boundaries and identification of inclusions within the predominant soil series (Baumgardner et al., 1985). Important soil properties for crop growth related to water holding capacity and fertility can be indirectly estimated by remote sensing of vegetation. Spatial patterns in remotely sensed images and crop yield maps over several years have been analyzed to identify areas within fields with similar crop responses (Gish et al., 2002). These homogenous zones may be used to guide soil sampling and form the basis for adjusting nutrient application rates using variable rate technology.

Crop residue management is an integral component of most conservation tillage systems. The Conservation Technology Information Center (CTIC) has defined conservation tillage as any tillage and planting system that has >30% residue cover after planting (CTIC, 2004). Annual assessments of crop residue cover and tillage practices in selected counties are compiled from roadside surveys in selected counties of the U.S. These surveys are subjective and the techniques vary from county to county (Thoma et al., 2004). No program exists for objectively monitoring tillage over broad areas.

Remote sensing provides efficient and objective methods of obtaining information about crop conditions cover over large areas (e.g., Bauer, 1985; Doraiswamy et al., 2001). Robust spectral vegetation indices have been developed to quantify green vegetation by exploiting the characteristic shape of the green vegetation spectrum with its high reflectance of the near infrared (700–1000 nm) and its low reflectance of the visible (400–700 nm). However, development of remote sensing indices for assessing crop residue cover has been impeded, because soils and crop residues lack unique spectral signatures in the 400–1100 nm region (Aase and Tanaka, 1991). Crop residues and soils are often spectrally similar and differ only in amplitude at a given wavelength. Shortly after harvest, crop residues are frequently much brighter than the soil, but as the residues weather and decompose they may be either brighter or darker than the soil (Nagler et al., 2000). This makes discrimination between crop residues and soil difficult or nearly impossible using reflectance techniques in the visible and near infrared wavelengths.

Efforts to enhance the discrimination of crop residues from soil have led to numerous spectral indices that incorporate the Landsat Thematic Mapper (TM) shortwave infrared bands (McNairn and Protz, 1993; van Deventer et al., 1997; Qi et al., 2002). However, these broadband spectral indices were only weakly correlated to crop residue cover (Daughtry et al., 2005).

An alternative approach for discriminating crop residues from soils is based on a broad absorption band near 2100 nm that is associated with cellulose and lignin in crop residues (Daughtry, 2001). The cellulose absorption index (CAI) was linearly related to crop residue cover in laboratory and field studies using ground-based spectroradiometer (Nagler et al., 2003; Daughtry et al., 2004). Tillage intensity classes were correctly identified in >90% of the fields in a limited test using aircraft hyperspectral imagery (Daughtry et al., 2005). For repetitive regional surveys of soil management practices satellite hyperspectral imagery is needed. However, the CAI algorithm has not been rigorously evaluated using satellite hyperspectral imaging systems. The Hyperion imaging spectrometer (<http://eol.gsfc.nasa.gov/Technology/Hyperion.html>) on the NASA Earth Observing-1 (EO-1) spacecraft appears to provide the appropriate spectral and spatial resolution for assessing crop residue cover.

Our objectives were: (1) to evaluate several spectral indices for estimating crop residue cover using the Landsat TM and Hyperion imaging spectrometer data over an agricultural region and (2) to classify tillage intensity in agricultural fields based on spectral measures of crop residue cover.

## 2. Materials and methods

### 2.1. Site description

The test site was a 7.5 km × 60 km area that included portions of Story, Boone and Hamilton counties in central Iowa (Fig. 1). Soils were formed in calcareous loamy glacial till on till plains and glacial moraines. Typical soil catena included Clarion (fine-loamy, mixed, superactive and mesic Typic Hapludoll), Nicolett (fine-loamy, mixed, superactive and mesic Aquic Hapludoll) and Webster (fine-loamy, mixed, superactive and mesic Typic Endoaquoll). Mean annual air temperature is 9 °C and mean annual precipitation is 866 mm. Corn and soybeans were grown on >96% of the cropland in 2003 (NASS, 2004). Planting progress for central Iowa was extracted from Iowa Crops and Weather (Iowa Agricultural Statistics, 2004). Expected

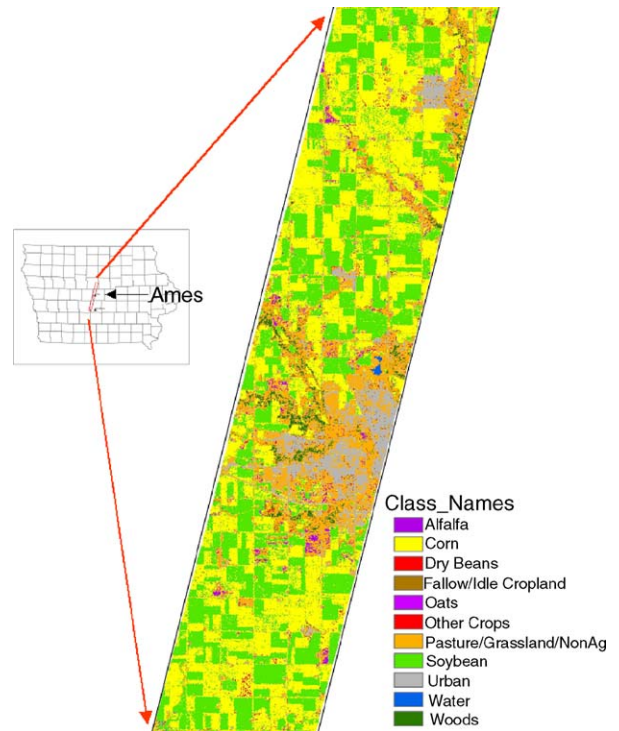


Fig. 1. Location of test site and crops in 2003. Crop identification based on classification of Landsat TM imagery by USDA National Agricultural Statistics Service (NASS, 2004). Classification accuracy exceeded 90%.

residue cover was estimated as  $f_R = 1 - \exp(-A_m M)$ , where  $f_R$  is the residue cover fraction,  $A_m$  the residue area per unit mass (ha/kg) and  $M$  is the residue mass per unit area (kg/ha).  $A_m = 0.0004$  ha/kg for corn and 0.0006 ha/kg for soybean (Gregory, 1982). Expected residue mass was calculated using reported 2003 grain yields (NASS, 2004) and harvest indices (grain mass/total above ground mass) of 0.52 for corn (Bullock et al., 1988) and 0.6 for soybean (Kollenkark et al., 1982).

### 2.2. Field methods

Crop residue cover was measured during 10–12 May 2004 in 35 corn and 19 soybean fields >20 ha. Two random locations per field were selected that were >100 m from field edges, >100 m apart (total number of sites = 108) and relatively homogeneous. At each site, a 15.2 m line-point transect with 100 evenly spaced markers was stretched diagonally across the rows and the number of markers intersecting crop residue was counted (Morrison et al., 1993). For the second measurement at each site, one end of the line-point transect was rotated ~90° in azimuth and the number of markers intersecting crop residue was recounted.

Vertical and oblique photographs plus notes on tillage condition were acquired at each site. A wide area augmented system (WAAS) enabled GPS receiver (Etrex Vista, Garmin International, Olathe, KS, USA) recorded the position of the center of each pair of line-point transects. Fields that had both corn and soybean residues were identified according to the crop grown in 2003.

### 2.3. Remotely sensed data

Landsat TM 5 data were acquired on 12 June 2004, geo-registered, and converted to apparent reflectance (ERDAS, 2003). All pixels that had a majority of their area within 45 m of the center of each pair of line-point transect measurements were selected and mean reflectance in each band was calculated. Four spectral indices designed for detecting crop residues using mean normalized difference tillage index (NDTI; van Deventer et al., 1997);

$$\text{NDTI} = \frac{\text{TM5} - \text{TM7}}{\text{TM5} + \text{TM7}} \quad (1)$$

normalized difference index (NDI; McNairn and Protz, 1993);

$$\text{NDI5} = \frac{\text{TM4} - \text{TM5}}{\text{TM4} + \text{TM5}} \quad (2)$$

$$\text{NDI7} = \frac{\text{TM4} - \text{TM7}}{\text{TM4} + \text{TM7}} \quad (3)$$

and normalized difference senescent vegetation index (NDSVI; Qi et al., 2002);

$$\text{NDSVI} = \frac{\text{TM5} - \text{TM3}}{\text{TM5} + \text{TM3}} \quad (4)$$

where TM3, TM4, TM5 and TM7 are reflectance in the Landsat TM band 3 (630 nm), band 4 (760–900 nm), band 5 (1550–1750 nm) and band 7 (2080–2350 nm), respectively.

The Hyperion imaging spectrometer on the NASA Earth Observing-1 spacecraft provides 220 bands at ~10 nm intervals over the 400–2500 nm wavelength region with a 30 m spatial resolution (<http://eol.gsfc.nasa.gov/Technology/Hyperion.html>). Each scene covers a 7.5 km × 100 km area. Hyperspectral images were acquired over the test site on 3 May and 4 June 2004. Each image was geo-registered with a root mean square error (rmse) of <1 pixel (<30 m). Three targets within the scene (a lake, an athletic field and parking lot) were used with the generic spectral signatures from the ERDAS/Imagine spectral library (ERDAS, 2003) to convert the digital numbers (DN) into apparent

reflectance. All pixels that had a majority of their area within 45 m of the center of each pair of line-point transect measurements were selected and the mean reflectance spectrum for each location was calculated. The CAI (Daughtry, 2001) was calculated using the corrected Hyperion data as follows:

$$\text{CAI} = 0.5(R_{2,0} + R_{2,2}) - R_{2,1}, \quad (5)$$

where  $R_{2,0}$  is the mean reflectance in three bands centered at 1982, 1992 and 2002 nm,  $R_{2,1}$  the mean reflectance in three bands centered at 2103, 2113 and 2123 nm and  $R_{2,2}$  is the mean reflectance in three bands centered at 2194, 2204 and 2214 nm.

Crop residue cover was described as a function of the various spectral indices using linear regression analysis (Proc REG; SAS Inst, 2004). Classification accuracy was evaluated using the Kappa analysis technique (Congalton and Green, 1999).

### 3. Results and discussion

The distribution of crops in the test site in 2003 as reported by the USDA National Agricultural Statistics Service (NASS) is shown in Fig. 1. Corn and soybeans accounted for >96% of the cropland. Mean 2003 grain yield was 10.5 Mg/ha for corn and 2.1 Mg/ha for soybeans in the Central Crop Reporting District of Iowa (NASS, 2004). Expected average crop residue cover after harvest was 98% for corn fields and 56% for soybean fields (Gregory, 1982). However, by mid-May 2004 when we measured residue cover with the line-point transect, decomposition and tillage had reduced mean crop residue cover to  $41 \pm 20\%$  for corn and  $21 \pm 19\%$  for soybean fields. Crop residue cover measured with line-point transects in these fields varied greatly and ranged from 8 to 84% for corn and 6 to 76% for soybeans. Clearly, tillage practices used by each farmer significantly influenced the amount of crop residue cover in fields. Thus, crop residue cover estimated for the average condition of a crop reporting district failed to capture the actual variability in crop residue cover from field to field, even within a relatively homogeneous agricultural region.

Crop residue cover changed rapidly during April, May and June as the fields were prepared and planted. Warm dry weather conditions in mid-April 2004 allowed farmers in central Iowa to accelerate seed bed preparation and begin corn planting ahead of normal (Table 1). Spring planting progressed rapidly until rains slowed field activities in the later half of May. In central Iowa, 93% of the corn area was planted by May 9 and 95% of the soybean area was planted by May

Table 1  
Field work and crop progress in central Iowa 2004 (Iowa Crops and Weather, 2004)

Week ending	Seed bed preparation (%)	Corn planted (%)	Soybean planted (%)	Days suitable	Rain (mm)
April 18	73	24	0	6.2	11
April 25	79	48	0	2.8	43
May 2	92	80	6	5.0	3
May 9	95	93	53	6.1	7
May 16	>99	>99	84	3.5	18
May 23	100	100	95	3.2	140
May 30	100	100	96	0.6	48
June 6	100	100	100	4.2	2
June 13	100	100	100	3.6	32

23 (Table 1). After a field was planted, its residue cover should have remained stable for several weeks as the crop emerged and began to grow.

Crop residue cover was weakly related to three of the four Landsat TM residue/tillage indices (Fig. 2). The NDSVI accounted for half of the variation in measured crop residue cover. Similar results were reported using these Landsat TM residue/tillage indices in Minnesota (Thoma et al., 2004) and Maryland (Daughtry et al.,

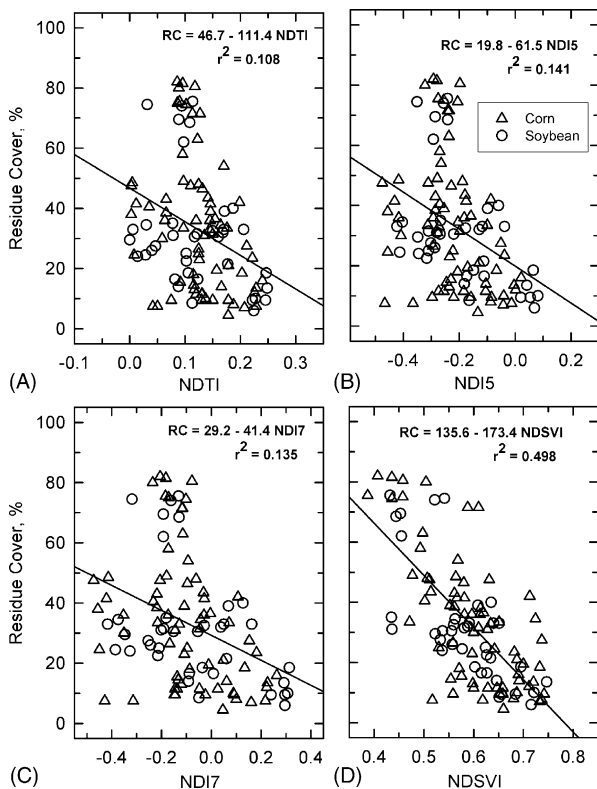


Fig. 2. (A–D) Crop residue cover as functions of Landsat residue/tillage indices.

2005). The quasi-physical Crop Residue Index Multi-spectral model (Baird and Baret, 1997), a linear mixing model of composite soil and crop residue reflectance, was also weakly related to residue cover (Thoma et al., 2004). Landsat-based spectral indices were generally poor predictors of crop residue cover for the conditions in this study.

In order to evaluate CAI for assessing crop residue cover, data were divided by fields into calibration ( $n = 38$ ) and test ( $n = 70$ ) data sets. For the calibration data set, crop residue cover was linearly related to CAI with coefficients of determination ( $r^2$ ) of 0.85 for the May and 0.77 for the June Hyperion data (Fig. 3). Soybean fields typically had lower residue covers than corn fields; however, crop type did not significantly affect the regression line (i.e., slopes were not significantly different at  $\alpha = 0.1$ ). Slopes in Fig. 3 were similar (within 10%) to that reported for ground-based spectroradiometer data in Maryland (Daughtry et al., 2005). Regression equations from the calibration data (Fig. 3) were used to predict residue cover for the test data (Fig. 4). Although there was considerable scatter about the 1:1 line, intercepts did not differ significantly from 0 and slopes were not significantly greater than 1.0 ( $\alpha = 0.1$ ). Root mean square errors were 9.5–11.7% for both calibration (Fig. 3) and test (not shown) data sets. Slopes and intercepts for the combined data sets ( $n = 108$ ) were not significantly different ( $\alpha = 0.1$ ) from slopes and intercepts of the calibration data sets ( $n = 38$ ). A portion of the scatter in Figs. 3 and 4 may be attributed to changes in residue cover that occurred between the time of the Hyperion data

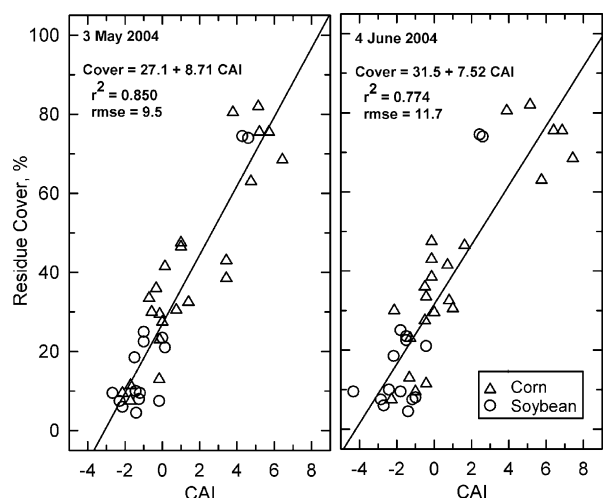


Fig. 3. Crop residue cover as a function of CAI for Hyperion data acquired on: (a) 3 May 2004 and (b) 4 June 2004. Calibration data set ( $n = 36$ ).



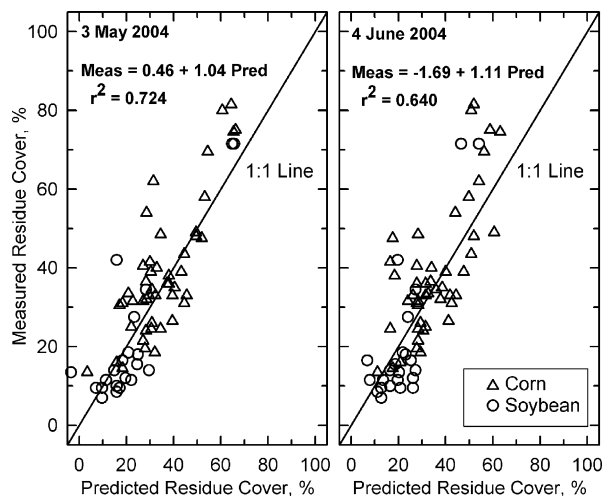


Fig. 4. Measured and predicted crop residue cover using Hyperion data acquired on: (a) 3 May 2004 and (b) 4 June 2004. Test data set ( $n = 72$ ).

acquisitions and the time of ground observations of residue cover. In central Iowa, 11.6 days were suitable for field work during the 2 weeks ending 9 May (Table 1). Seed bed preparation was nearly complete and >80% of the corn had been planted before the Hyperion overpass on 3 May 2004. Nearly all the corn and soybean cropland in central Iowa was planted before the 4 June 2004 Hyperion overpass. Of the 54 fields that we observed, 51 were planted by 10–12 May 2004.

Table 2 presents a classification matrix for four residue cover classes using CAI for the May and June Hyperion data. Both May ( $Z$  score = 8.0) and June ( $Z$  score = 5.9) classifications were significantly better than a random classification using the Kappa analysis technique (Congalton and Green, 1999). Classification matrices for fewer classes can be determined by combining classes in Table 2. CTIC (2004) defined the following tillage categories based on crop residue cover after planting: intensive tillage as <15% residue

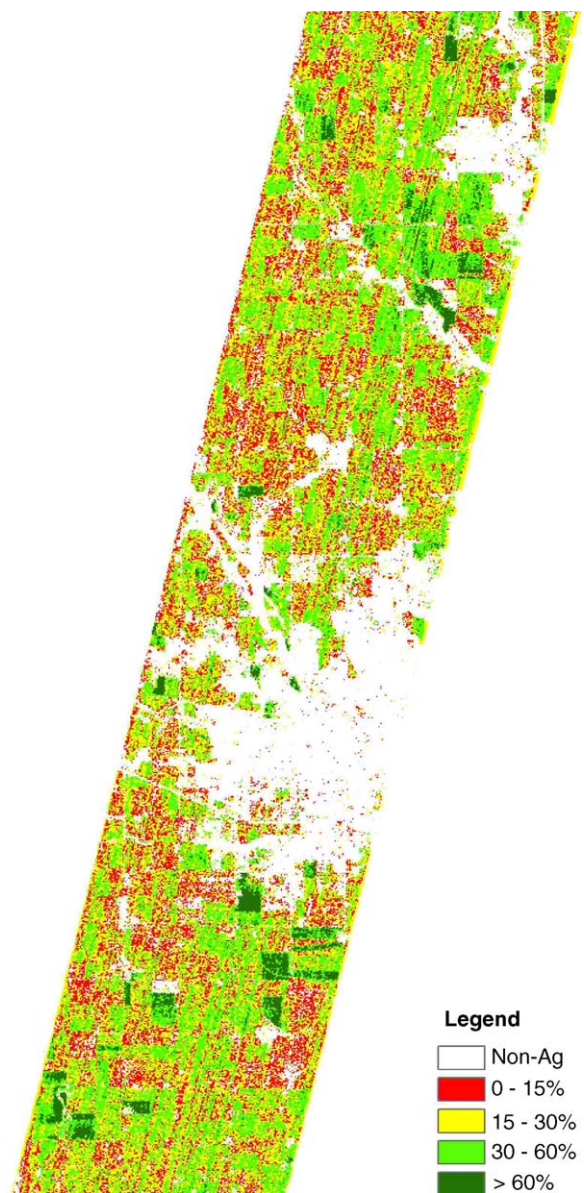


Fig. 5. Cropland classified into four crop residue cover categories using CAI from Hyperion data for 3 May 2004.

Table 2

Classification matrix for four residue cover classes derived from Hyperion data for 3 May and 4 June 2004

Measured cover class (%)	$n$	3 May				4 June			
		<15% <sup>a</sup>	15–30% <sup>a</sup>	30–60% <sup>a</sup>	≥60% <sup>a</sup>	<15% <sup>a</sup>	15–30% <sup>a</sup>	30–60% <sup>a</sup>	≥60% <sup>a</sup>
<15	27	<b>15</b>	12	0	0	<b>11</b>	16	0	0
15–30	24	1	<b>18</b>	5	0	1	<b>19</b>	4	0
30–60	41	0	17	<b>24</b>	0	0	16	<b>24</b>	1
≥60	16	0	0	3	<b>13</b>	0	0	9	<b>7</b>

Correct classifications are shown in bold (total  $n = 108$ ).

<sup>a</sup> Remotely sensed residue cover classes.

Table 3  
Crop residue cover classes derived from Hyperion data for 3 May and 4 June 2004

Crop in 2003	3 May				4 June			
	<15% <sup>a</sup>	15–30% <sup>a</sup>	30–60% <sup>a</sup>	≥60% <sup>a</sup>	<15% <sup>a</sup>	15–30% <sup>a</sup>	30–60% <sup>a</sup>	≥60% <sup>a</sup>
Corn	4791	9831	11271	1398	4549	9441	12005	1225
Soybean	7223	8362	4883	364	6888	8344	5338	234
Other	559	692	391	15	496	713	430	15
Total	12573	18885	16545	1777	11933	18498	17772	1475
Area (%)	25.3	37.9	33.2	3.6	24.0	37.2	35.8	3.0

All values are in hectares.

<sup>a</sup> Remotely sensed residue cover classes.

cover, reduced tillage as 15–30% residue cover and conservation tillage as ≥30% residue cover. In Table 2, we divided the conservation tillage category into 30–60 and ≥60% residue cover classes to identify fields managed for high residue cover (and possibly high C sequestration).

Percent correct classifications for multiple residue cover classes improved as the number of classes decreased. The difference in accuracy between the May and June classifications were not significant using the Kappa analysis technique (Congalton and Green, 1999). Accuracies were 57–65% for discriminating among four tillage categories. Accuracies were 66–68% for discriminating among intensive, reduced and conservation tillage categories. For discriminating two categories (i.e., conventional or conservation tillage, <30 or ≥30% cover), accuracies were 80–82%. Thoma et al. (2004) showed that various methods of predicting crop residue cover using Landsat data had accuracies of 61–69% which were as good or better than the Tillage Transect Survey (TTS) estimates when fields were grouped into only two residue cover categories. Human observers used in the TTS often had difficulty distinguishing small differences in residue cover near the 30% threshold used to discriminate conventional and conservation tillage (Thoma et al., 2004). The oblique viewing angles typically used by the TTS observers probably contributed to the relatively poor classification accuracy. Remote sensing techniques can provide a uniform methodology and cover large areas completely rather than sampling a few fields along transects in selected counties.

Crop residue cover for both Hyperion scenes was estimated using the calibration equations (Fig. 3) and summarized in four residue classes (Fig. 5). Data from crop type in 2003 (Fig. 1) and crop residue cover after planting in 2004 (Fig. 5) were combined and summarized as the areas in four residue cover classes for each crop (Table 3). Since the May and June

classifications were not significantly different, only the May data will be discussed. Overall, 37% of the cropland was classified as conservation tillage (≥30% cover), 38% was classified as reduced tillage (15–30% cover) and 25% was classified as intensively tilled (<15% cover). For cropland that was corn in 2003, 46% was classified as conservation tillage after planting in 2004 and only 18% as intensive tillage. Although soybean produced much less crop residue mass than corn, 25% of the cropland planted to soybeans in 2003 was classified as conservation tillage after planting in 2004 and 35% as intensive tillage. Shifts in soil tillage intensity over time and space could be tracked by combining geo-referenced information on the previous crop type with geo-referenced information on crop residue cover after planting.

#### 4. Conclusions

While remote sensing cannot directly monitor soil C dynamics, it can provide crucial information associated with above ground net primary production including land use, crop type, crop phenology, leaf area index and absorbed photosynthetically active radiation. Crop residue cover and thus soil tillage intensity may be determined by advanced remote sensing techniques. These inputs for soil C models, when implemented within a geographic information system, provide important boundary conditions on the dynamics of soil organic matter across landscapes.

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